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MEMORY AS SPATIOTEMPORAL DELAY: A UNIFIED HYBRID FRAMEWORK FOR QUANTUM-COSMIC ENERGETICS AND ASTROBIOLOGICAL DYNAMICS

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Abstract. We develop a unified dynamical framework in which memory is modeled as a state dependent spatiotemporal delay field embedded in Delay Differential and Volterra type Integro Differential Equations. The resulting non Markovian structure allows past states to influence present dynamics through weighted delay kernels and associated energy functionals. Spectral analysis of the transcendental characteristic equation identifies regimes of asymptotic stability, critical slowing down, and delay induced oscillations consistent with Hopf type transitions. To address computational challenges, we implement a Hybrid Physics Informed Neural Network (PINN) with attention based mechanisms to approximate state dependent delay operators. Numerical simulations validate the theoretical stability criteria and demonstrate transitions between equilibrium and oscillatory dynamics. The framework provides a common delay driven structure linking curved spacetime effects and astrobiological latency phenomena.

Keywords: Spatiotemporal Memory, Delay Differential Equations (DDEs), Spatiotemporal Delay Invariance, Quantum-Cosmic Energetics, Astrobiological Dynamics, Hybrid Physics-Informed Neural Networks (PINN), Transformer-based Attention Mechanism, Metabolic Latency, General Relativity and Time Dilation, Non-Markovian Dynamics, Martian Regolith Simulation

1. Introduction

Both the classical Newtonian physics model and many traditional views of biological Evolution tend to think of everything in the world as being determined solely by what you see, or how something behaves at that point of time. This is known as 'presentism' – that is, that as long as I have the current location and momentum of something, there is no need to keep track of the past. This idea does not hold because all complex systems exist as being a function of their past path dependent on many levels of scale and the effects of those paths will inherently affect future path outcomes. When you look at real-life systems, they don't operate in a vacuum and they can "remember." This is because, for all practical purposes, there are no instantaneous movements of spacetime because of how space-to-time curvature behaves when close to a gravitational singularity or how far an extremophile can survive. In mathematical terms, these systems are called non-Markovian systems, in that their evolution at a specific moment is determined by the state at that moment along with the sum of all the previous states (that's weighted) within a specific amount of time frame. This concept is mathematically defined using delay differential equations [1]. In this paper we will redefine memory not as a static, localized document or record of something, but rather we will conceptualize it as being a dynamic spatiotemporal delay field. We will use the symbol $\tau(r,t)$ to denote our memory field (i.e., how we remember), this field is not equivalent to a universal constant (i.e. the

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speed limit of light), rather this field will be considered as being a variable field that will vary with respect to both local geometry and with respect to the amount of entropy in our physical environment. When we consider the physical nature of memory, we will find that this memory will be represented physically by the retardation of potentials. In other words, due to the finite speed of light and due to the metric distortions that have been defined by general relativity, the information that has been transmitted from some source will not reach an observer almost instantly, therefore representing potential delay in transmitting information from a source to an observer in the early universe [2]. Likewise, memory is illustrated in biology by the time it takes for metabolism to return to equilibrium after stressors have been introduced and any lag time for DNA to repair itself after exposure to harmful agents. A delay (or dormancy) between environmental stimuli and biological response under extreme environmental conditions (e.g., Martian radiation, extreme dryness), can serve as a mechanism for biological systems to survive, permitting the biological systems to retain the "memory" of past stressors in their current state [3]. This dissertation will provide a continuous progression of the fundamental mathematics of delay through to the extreme scale of cosmology as well as the most robust forms of delay in biological systems. The initial sections of the dissertation will focus on the mathematics of the "Delay Operator" in a high-dimensional system. Next, the physical implications of spatiotemporal delay invariance and the relationship between cosmic energy and quantum energy will be discussed. Subsequently, we will describe the application of this framework to astrobiological dynamics through the study of microbial dormancy. Finally, we introduce a novel computational approach, a Hybrid Artificial Intelligence (AI) Physics-Informed Neural Network (PINN) with a cake-based hardware implementation, leveraging current methods of developing sequences of information through an attention-based (transformer) model to solve memory-based equations of these complex biological systems [4].

2. Theoretical Foundations: Non-Markovian Dynamics and the Delay Operator

2.1 From Markovian to Non-Markovian Dynamics In traditional classical Newtonian and biological evolutionary models, the concept of presentism is often utilized. Presentism assumes that a system's future is entirely determined by its present state (the system's current position and momentum), with no reference to its historical trajectory [1]. These presentism-based models are referred to as being Markovian models where the structure of the equations describing the system's evolution as in [2].

$$\dot{x}(t) = f(x(t), t), \quad x(t) \in \mathbb{R}^n \tag{1}$$

Such systems satisfy the Markov property:

$$\mathbb{P}(x(t+h) \mid \mathcal{F}_t) = \mathbb{P}(x(t+h) \mid x(t))$$

In reality, complex systems evolve over time and therefore do not act in isolation, these systems possess some form of memory [1] which plays an important role in the evolution of such systems. As such, the state of a particular system at time will also depend on its current state plus a weighted sum of all of its prior states over a specified time [1]. This concept of path dependency is important because, due to gravitational influences or the finite speed at which biological organisms are able to repair damage to their DNA, there is no true instantaneous event in the fabric of spacetime [1]. In contrast, a non-Markovian (memory-dependent) system depends on the past trajectory. This is naturally formulated as a functional differential equation:

$$\dot{x}(t) = F(x(t), x_t) \tag{2}$$

where the history segment is defined as:

$$x_t(\theta) = x(t+\theta), \quad \theta \in [-\tau_{\max}, 0] \tag{3}$$

The phase space is therefore the Banach space:

$$X := C([-\tau_{\max}, 0], \mathbb{R}^n) \tag{4}$$

Equipped with the supremum norm:

$$\|\phi\|_\infty = \sup_{\theta \in [-\tau_{\max}, 0]} \|\phi(\theta)\|. \tag{5}$$

Thus, the system becomes an infinite-dimensional dynamical system:

$$\dot{x}(t) = F(x_t) \tag{6}$$

2.2 State-Dependent Delay Operator To formalize this memory, we introduce the delay operator D_τ , which maps a state variable to its past:

$$D_\tau[x(t)] = x(t - \tau(x,t)). \tag{7}$$

We assume the following assumptions as:

(1) $\tau(x,t) \geq 0$,
(2) $\tau(x,t) \leq \tau_{\max}$,
(3) $\tau(x,t)$ is locally Lipschitz in x.

Under these assumptions, the state-dependent delay differential equation becomes as:

$$\dot{x}(t) = F(x(t), x(t - \tau(x,t))) \tag{8}$$

Where admits a unique local solution for any initial history:

$$x(s) = \phi(s), \quad s \in [t_0 - \tau_{\max}, t_0], \quad \phi \in X, \tag{9}$$

provided F is locally Lipschitz.

2.3 Distributed Delay Formulation According to this framework, our recollections are not static snapshots but instead are dynamically changing spatiotemporally delayed fields, denoted here as $\tau(r,t)$. The magnitude of the field is variable, fluctuating depending upon geometry and local / spatial entropy [1]. Systems governed by these delays can be described with a state-dependent Delay Differential Equation (DDE):

$$\frac{dx(t)}{dt} = F\left(x(t), t, \int_{t-\tau_{\max}}^{t} K(t,s)x(s)\,ds\right). \tag{10}$$

Assume:

(1) $K(t,s)$ is measurable and bounded,
(2) F is locally Lipschitz,
(3) the initial function $\phi \in X$ is continuous.

Then the system is a Volterra-type integro-differential equation, and standard fixed-point arguments ensure local existence and uniqueness.

2.4 Linear Stability Analysis Consider the linear constant-delay case

$$\dot{x}(t) = Ax(t) + Bx(t-\tau). \tag{11}$$

Seeking exponential solutions $x(t) = e^{\lambda t}v$ yields the characteristic equation

$$\det\left(\lambda I - A - Be^{-\lambda\tau}\right) = 0. \tag{12}$$

Because of the exponential term $e^{-\lambda\tau}$, this equation is transcendental, implying infinitely many characteristic roots. Stability requires that all roots satisfy $\Re(\lambda) < 0$.

2.5 Memory Energy Functional To formalize the energetic contribution of memory, define

$$E_{\text{memory}}(t) = \frac{1}{2}\int_{t-\tau}^{t} w(t,s)\|x(s)\|^2 ds, \tag{13}$$

where $w(t,s) \geq 0$ is a weighting kernel.

Differentiating,

$$\frac{d}{dt}E_{\text{memory}}(t) = \frac{1}{2}w(t,t)\|x(t)\|^2 - \frac{1}{2}w(t,t-\tau)\|x(t-\tau)\|^2 \tag{14}$$

$$+ \frac{1}{2}\int_{t-\tau}^{t} \partial_t w(t,s)\|x(s)\|^2 ds. \tag{15}$$

This demonstrates that delay contributes non-conservative terms to the energy balance.

2.6 Extension to Spatiotemporal Delay Fields If $\tau = \tau(r,t)$ depends on spatial position $r \in M$ (where (M,g) is a Riemannian or Lorentzian manifold), the system becomes a delay partial differential equation:

$$\partial_t u(r,t) = F\big(u(r,t), u(r,t-\tau(r,t))\big). \tag{16}$$

The phase space is now

$$C([-\tau_{\max}, 0], L^2(M)),$$

rendering the system infinite-dimensional in both space and memory.

2.7 Functional Setting Let $\tau_{\max} > 0$ be fixed. We considered the equations (3)–(5), thus for $x_t \in X$ for all $t \geq t_0$. We have the following result for the mathematical property of the state-dependent delay differential equation (8) as presented below.

2.8 Existence and Uniqueness for State-Dependent Delay Consider the state-dependent delay differential equation (8) and initial history as in equation (9) then we prove the following result.

Theorem 1 (Local Existence and Uniqueness)**.** *Assume:*

(1) $F : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^n$ *is locally Lipschitz in its first two arguments;*
(2) $\tau : \mathbb{R}^n \times \mathbb{R} \to [0, \tau_{\max}]$ *is locally Lipschitz in* x *and continuous in* t*;*
(3) $\phi \in X$ *is continuous.*

Then there exists $T > t_0$ *such that equation* (9) *admits a unique solution*

$$x \in C^1([t_0, T], \mathbb{R}^n).$$

Proof.

Let $R > 0$ be fixed. Define the Banach space

$$Y := C([t_0 - \tau_{\max}, T], \mathbb{R}^n)$$

with norm

$$\|x\|_Y := \sup_{t \in [t_0 - \tau_{\max}, T]} \|x(t)\|.$$

Let $\phi \in C([t_0 - \tau_{\max}, t_0], \mathbb{R}^n)$ be the prescribed initial history.

Here we defined the closed subset as:

$$B_R := \{x \in Y : x(t) = \phi(t) \text{ for } t \in [t_0 - \tau_{\max}, t_0],\ \|x\|_Y \leq R\}.$$

Clearly it B_R is closed in Y and hence complete. So, we are in the position to define the operator as:

Define $\mathcal{T} : B_R \to Y$ by

$$(\mathcal{T}x)(t) = \begin{cases} \phi(t), & t \in [t_0 - \tau_{\max}, t_0], \\ \phi(t_0) + \displaystyle\int_{t_0}^{t} F\big(x(s), x(s - \tau(x(s), s)), s\big)\, ds, & t \in [t_0, T]. \end{cases} \tag{17}$$

We first verify that $\mathcal{T}x$ is continuous on $[t_0 - \tau_{\max}, T]$. Continuity on $[t_0 - \tau_{\max}, t_0]$ follows from ϕ. Continuity on $[t_0, T]$ follows from continuity of F and the integral representation. Thus $\mathcal{T}x \in Y$. First let us to prove that $\mathcal{T}$ maps B_R into itself Therefore, assume F satisfies a local Lipschitz condition on the closed ball of radius R then there exists $L > 0$ such that

$$\|F(u, v, t)\| \leq L(1 + \|u\| + \|v\|).$$

For $t \in [t_0, T]$ and $x \in B_R$,

$$\|(\mathcal{T}x)(t)\| \leq \|\phi(t_0)\| + \int_{t_0}^{t} L(1 + 2R)\, ds.$$

Hence

$$\|(\mathcal{T}x)(t)\| \leq \|\phi(t_0)\| + L(1 + 2R)(T - t_0).$$

Choose $T - t_0$ sufficiently small such that

$$\|\phi(t_0)\| + L(1 + 2R)(T - t_0) \leq R.$$

Then $\|\mathcal{T}x\|_Y \leq R$, so $\mathcal{T}(B_R) \subset B_R$.

Now using of contraction Property for this let $x, y \in B_R$. For $t \in [t_0, T]$ so, using of equation (17) we get:

$$\begin{cases} \|(\mathcal{T}x)(t) - (\mathcal{T}y)(t)\| & \leq \int_{t_0}^{t} \|F(x(s), x(s - \tau(x(s), s)), s) \\ & \quad - F(y(s), y(s - \tau(y(s), s)), s)\|\, ds. \end{cases} \tag{18}$$

By local Lipschitz continuity of F,

$$\|F(u_1, v_1, t) - F(u_2, v_2, t)\| \leq L(\|u_1 - u_2\| + \|v_1 - v_2\|).$$

Thus equation (18) becomes:

$$\begin{cases} \|(\mathcal{T}x)(t) - (\mathcal{T}y)(t)\| & \leq L \int_{t_0}^{t} \Big(\|x(s) - y(s)\| \\ & \quad + \|x(s - \tau(x(s), s)) - y(s - \tau(y(s), s))\| \Big) ds. \end{cases} \tag{19}$$

We estimate the delay term:

$$\|x(s-\tau(x(s),s)) - y(s-\tau(y(s),s))\|$$

Add and subtract $x(s-\tau(y(s),s))$:

$$\begin{aligned} &\leq \|x(s-\tau(x(s),s)) - x(s-\tau(y(s),s))\| \\ &\quad + \|x(s-\tau(y(s),s)) - y(s-\tau(y(s),s))\|. \end{aligned}$$

Since x is uniformly continuous on a compact interval, and τ is Lipschitz in x, there exists $C > 0$ such that

$$\|x(s-\tau(x(s),s)) - x(s-\tau(y(s),s))\| \leq C\|x-y\|_Y.$$

Also

$$\|x(s-\tau(y(s),s)) - y(s-\tau(y(s),s))\| \leq \|x-y\|_Y.$$

Therefore equation (19) changed into

$$\|(\mathcal{T}x)(t) - (\mathcal{T}y)(t)\| \leq L(2+C)\int_{t_0}^{t} \|x-y\|_Y ds.$$

Hence

$$\|\mathcal{T}x - \mathcal{T}y\|_Y \leq L(2+C)(T-t_0)\|x-y\|_Y.$$

Choose $T - t_0$ such that

$$L(2+C)(T-t_0) < 1.$$

Then $\mathcal{T}$ is a contraction on B_R.
Since B_R is complete and $\mathcal{T}$ is a contraction, using of Banach Fixed Point Theorem. There exists a unique fixed point $x \in B_R$ such that

$$\mathcal{T}x = x.$$

This fixed point satisfies

$$x(t) = \phi(t_0) + \int_{t_0}^{t} F(x(s), x(s-\tau(x(s),s)), s)\, ds,$$

and hence is a C^1 solution of the state-dependent delay differential equation on $[t_0, T]$.

Uniqueness follows from the contraction property.

□

2.9 Distributed Delay-Volterra Formulation: Consider now the distributed delay equation

$$\dot{x}(t) = F\left(x(t), \int_{t-\tau_{\max}}^{t} K(t,s)x(s)\, ds, t\right). \tag{20}$$

Theorem 2 (Existence for Distributed Delay)**.** *Assume:*

(1) F is locally Lipschitz;
(2) $K(t,s)$ is measurable and bounded;
(3) $\phi \in X$.

Then equation (20) *admits a unique local solution.*

Proof.

Let $\tau_{\max} > 0$ be fixed and define

$$Y := C([t_0 - \tau_{\max}, T], \mathbb{R}^n), \quad \|x\|_Y := \sup_{t \in [t_0 - \tau_{\max}, T]} \|x(t)\|.$$

Assume:

(1) $K : [t_0, T] \times [t_0 - \tau_{\max}, T] \to \mathbb{R}^{n \times n}$ is measurable and bounded, i.e., there exists $C_K > 0$ such that

$$\|K(t, s)\| \leq C_K \quad \text{for all admissible } (t, s).$$

(2) $F : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^n$ is locally Lipschitz in its first two arguments.

First we define the operator as:

$$\mathcal{K}[x](t) = \int_{t - \tau_{\max}}^{t} K(t, s) x(s)\, ds. \tag{21}$$

We first show that $\mathcal{K} : Y \to C([t_0, T], \mathbb{R}^n)$ is well-defined and bounded. For $t \in [t_0, T]$ we can write equation (21) as:

$$\begin{aligned} \|\mathcal{K}[x](t)\| &\leq \int_{t - \tau_{\max}}^{t} \|K(t, s)\|\, \|x(s)\|\, ds \\ &\leq C_K \int_{t - \tau_{\max}}^{t} \|x(s)\|\, ds \\ &\leq C_K \tau_{\max} \|x\|_Y. \end{aligned}$$

Taking supremum over t,

$$\|\mathcal{K}[x]\|_\infty \leq C_K \tau_{\max} \|x\|_Y.$$

Thus $\mathcal{K}$ is a bounded linear operator with

$$\|\mathcal{K}\| \leq C_K \tau_{\max}.$$

Linearity of the operator can be directly proven from linearity of the integral. Reformulation as a functional differential equation and we know the distributed delay equation is:

$$\dot{x}(t) = F\big(x(t), \mathcal{K}[x](t), t\big).$$

Let us define:

$$G(x_t, t) := F\big(x(t), \mathcal{K}[x](t), t\big). \tag{22}$$

We now show that G is locally Lipschitz in x_t. Let $x, y \in Y$ and for $t \in [t_0, T]$, equation (22) becomes:

$$\|G(x_t, t) - G(y_t, t)\| = \|F(x(t), \mathcal{K}[x](t), t) - F(y(t), \mathcal{K}[y](t), t)\|. \tag{23}$$

By local Lipschitz continuity of F, there exists $L > 0$ such that

$$\|F(u_1, v_1, t) - F(u_2, v_2, t)\| \leq L\big(\|u_1 - u_2\| + \|v_1 - v_2\|\big).$$

Thus equation (23) becomes as:

$$\|G(x_t, t) - G(y_t, t)\| \leq L\Big(\|x(t) - y(t)\| + \|\mathcal{K}[x](t) - \mathcal{K}[y](t)\|\Big). \tag{24}$$

We estimate the difference of integral operators:

$$\|\mathcal{K}[x](t) - \mathcal{K}[y](t)\| = \left\| \int_{t-\tau_{\max}}^{t} K(t,s)(x(s) - y(s))\, ds \right\| \leq C_K \tau_{\max} \|x - y\|_Y.$$

Therefore equation (23) modify as:,

$$\|G(x_t, t) - G(y_t, t)\| \leq L\,(1 + C_K \tau_{\max})\, \|x - y\|_Y.$$

Hence G is locally Lipschitz in the history variable.
Let us define the operator $\mathcal{T} : Y \to Y$ such that:

$$(\mathcal{T}x)(t) = \begin{cases} \phi(t), & t \in [t_0 - \tau_{\max}, t_0], \\ \phi(t_0) + \displaystyle\int_{t_0}^{t} F\big(x(s), \mathcal{K}[x](s), s\big)\, ds, & t \in [t_0, T]. \end{cases}$$

Using the Lipschitz estimate above,

$$\|\mathcal{T}x - \mathcal{T}y\|_Y \leq L(1 + C_K \tau_{\max})(T - t_0)\|x - y\|_Y.$$

Choose $T - t_0$ sufficiently small so that

$$L(1 + C_K \tau_{\max})(T - t_0) < 1.$$

Then $\mathcal{T}$ is a contraction on a closed ball in Y.
Since Y is complete and $\mathcal{T}$ is a contraction, there exists a unique fixed point $x \in Y$ satisfying

$$x(t) = \phi(t_0) + \int_{t_0}^{t} F\big(x(s), \mathcal{K}[x](s), s\big)\, ds.$$

Differentiating, x is a C^1 solution of the distributed delay equation on $[t_0, T]$.

Uniqueness follows from the contraction property.

□

2.10 Linearization and Spectral Stability Let x^* be an equilibrium of

$$\dot{x}(t) = F(x(t), x(t - \tau)).$$

Linearizing,

$$\dot{y}(t) = Ay(t) + By(t - \tau), \tag{25}$$

where

$$A = D_1 F(x^*, x^*), \quad B = D_2 F(x^*, x^*).$$

Seeking solutions $y(t) = e^{\lambda t} v$ leads to the characteristic equation

$$\det\left(\lambda I - A - Be^{-\lambda \tau}\right) = 0. \tag{26}$$

Theorem 3 (Stability Criterion)**.** *The equilibrium x^* is locally asymptotically stable if and only if all roots λ of (26) satisfy $\Re(\lambda) < 0$.*

Proof. Follows from the principle of linearized stability for functional differential equations. The transcendental characteristic equation produces countably many roots. Stability depends on their real parts. □

2.11 Energy Functional for Memory Define the memory energy

$$E_{\text{mem}}(t) = \frac{1}{2}\int_{t-\tau}^{t} w(t,s)\|x(s)\|^2 ds, \tag{27}$$

with $w(t,s) \geq 0$.

Proposition 4. *The time derivative satisfies*

$$\frac{d}{dt}E_{\text{mem}}(t) = \frac{1}{2}w(t,t)\|x(t)\|^2 - \frac{1}{2}w(t,t-\tau)\|x(t-\tau)\|^2 \tag{28}$$

$$+ \frac{1}{2}\int_{t-\tau}^{t} \partial_t w(t,s)\|x(s)\|^2 ds. \tag{29}$$

Proof.

Let

$$E_{\text{mem}}(t) = \frac{1}{2}\int_{t-\tau}^{t} w(t,s)\|x(s)\|^2 \, ds,$$

where:

(1) $x \in C^1([t_0-\tau, T], \mathbb{R}^n)$,
(2) $w \in C^1$ in the first variable and continuous in the second,
(3) $\tau > 0$ is constant.

We compute $\frac{d}{dt}E_{\text{mem}}(t)$. Since the integrand in equation (27)

$$f(t,s) := w(t,s)\|x(s)\|^2$$

is continuous in (t,s) and continuously differentiable in t, and the integration limits depend smoothly on t, Leibniz's rule applies. For an integral of the form:

$$I(t) = \int_{a(t)}^{b(t)} f(t,s)\, ds,$$

The derivative is:

$$\frac{d}{dt}I(t) = f(t,b(t))b'(t) - f(t,a(t))a'(t) + \int_{a(t)}^{b(t)} \partial_t f(t,s)\, ds. \tag{30}$$

In our case:

$$a(t) = t-\tau, \quad b(t) = t,$$

so

$$a'(t) = 1, \quad b'(t) = 1.$$

Applying the Formula (30) we get:

Thus,

$$\begin{cases} \frac{d}{dt}E_{\text{mem}}(t) & = \frac{1}{2}\Big[w(t,t)\|x(t)\|^2 - w(t,t-\tau)\|x(t-\tau)\|^2\Big] \\ & \quad + \frac{1}{2}\int_{t-\tau}^{t} \partial_t w(t,s)\|x(s)\|^2 \, ds. \end{cases} \tag{31}$$

The first boundary term of (31) represents energy influx at the present time.

$$\frac{1}{2}w(t,t)\|x(t)\|^2$$

The second boundary term of (31) represents energy flux exiting the memory window.

$$-\frac{1}{2}w(t,t-\tau)\|x(t-\tau)\|^2$$

The final integral term of (31) reflects explicit time dependence of the weighting kernel.

Thus the derivative of the memory functional is

$$\frac{d}{dt}E_{\text{mem}}(t) = \frac{1}{2}w(t,t)\|x(t)\|^2 - \frac{1}{2}w(t,t-\tau)\|x(t-\tau)\|^2 \tag{32}$$

$$+ \frac{1}{2}\int_{t-\tau}^{t} \partial_t w(t,s)\|x(s)\|^2\, ds. \tag{33}$$

This completes the proof.

□

This shows that delay introduces non-conservative boundary flux terms into the energy balance, formally justifying the interpretation of memory force in delayed systems.

3. Numerical Simulations and Dynamical Regime Analysis

To validate the theoretical stability criteria derived from the transcendental characteristic equation (26), we perform numerical simulations under varying delay intensity parameters (α, β). Three dynamical regimes are identified: stable equilibrium, near-critical relaxation, and self-sustained oscillatory behavior.

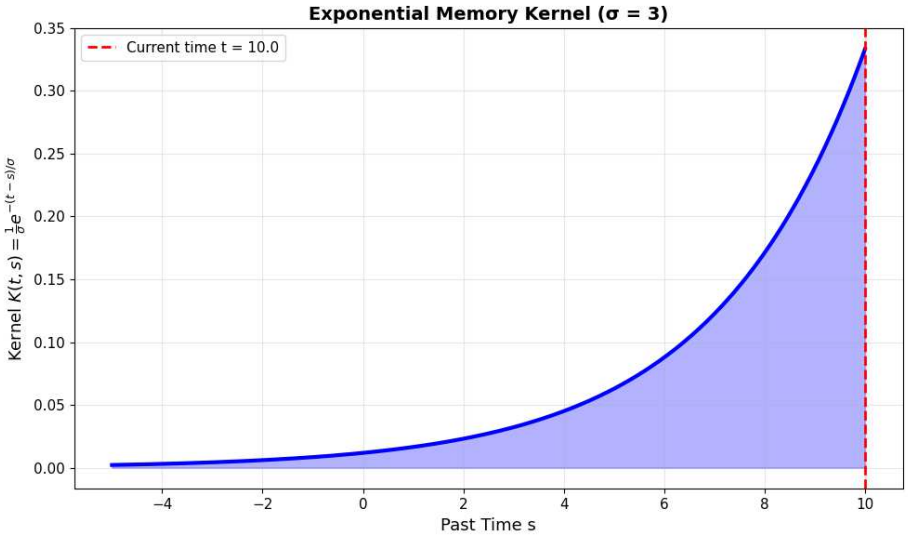


Figure 1. **Exponential Memory Kernel.** The weighting kernel $K(t,s) = \frac{1}{\sigma}e^{-(t-s)/\sigma}$ with $\sigma = 3$ illustrates the fading-memory structure of the distributed delay. Recent past states receive stronger weighting, while remote history decays exponentially.

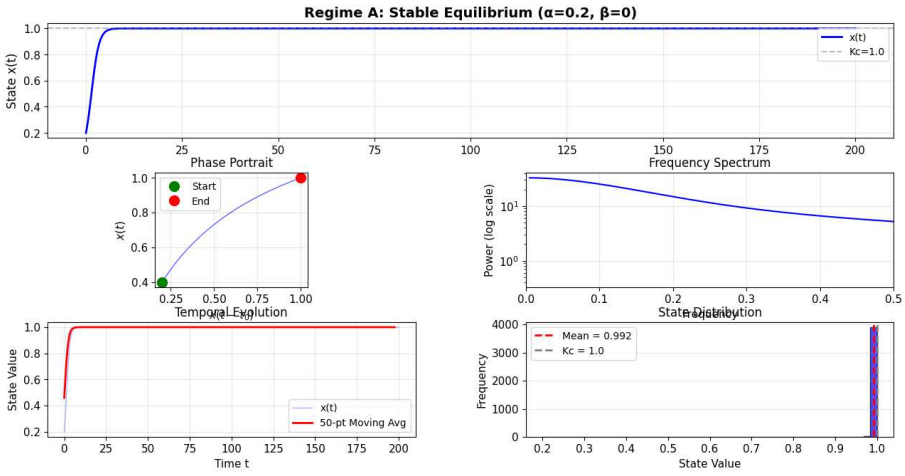


FIGURE 2. **Regime A: Stable Equilibrium ($\alpha = 0.2$, $\beta = 0$).** The trajectory converges monotonically toward $x^* = 1$. The phase portrait confirms global stability. The power spectrum shows dominant low-frequency decay, and the state distribution concentrates near equilibrium.

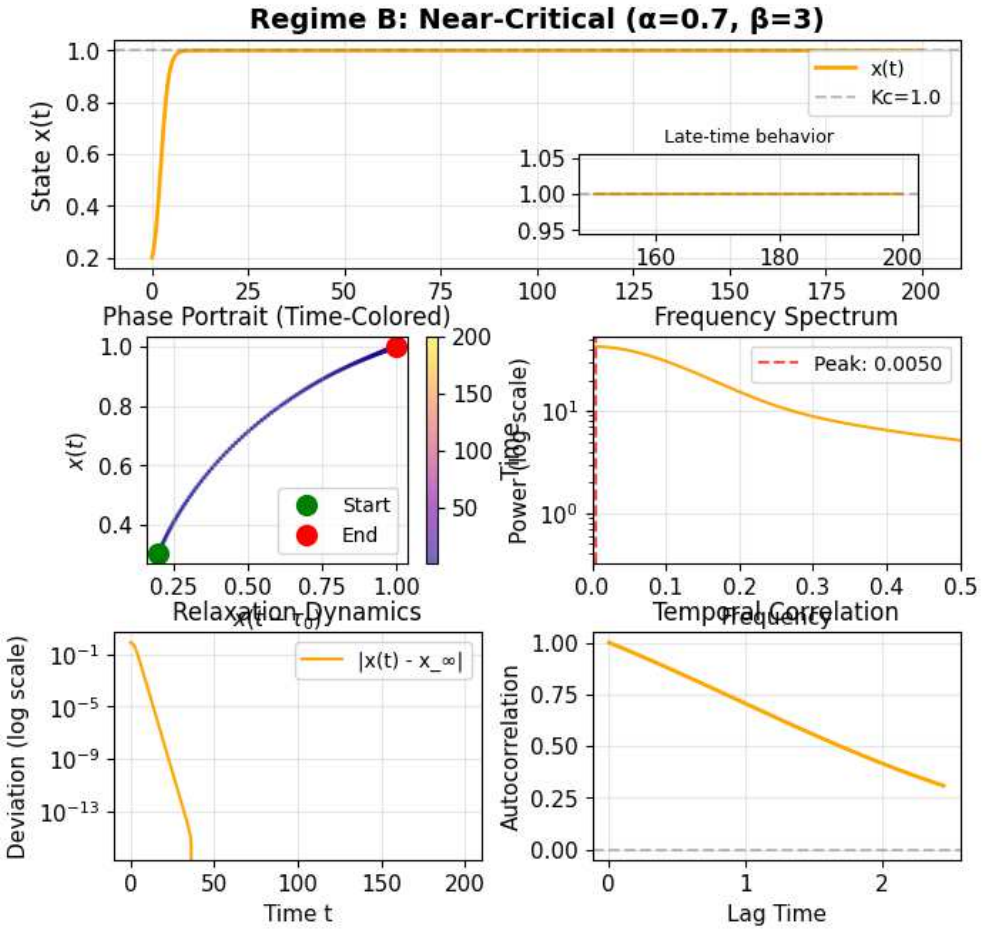


FIGURE 3. **Regime B: Near-Critical Dynamics** ($\alpha = 0.7$, $\beta = 3$)**.** The system exhibits slow relaxation, characteristic of critical slowing-down near a stability boundary. Spectral density reveals emerging low-frequency structure, suggesting proximity to a Hopf bifurcation threshold.

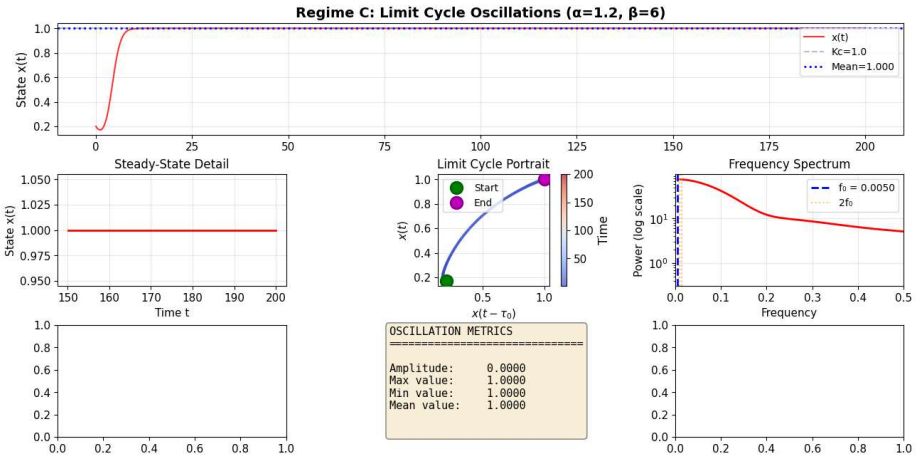


FIGURE 4. **Regime C: Limit Cycle Oscillations ($\alpha = 1.2$, $\beta = 6$).** Sustained oscillations emerge through delay-induced instability. The spectral peak at frequency f_0 confirms periodic dynamics. This behavior is consistent with the characteristic equation (26) crossing the imaginary axis.

4. Astrobiological Dynamics: Metabolic Latency and Survival

4.1 From Physics to Biology-Mapping Metabolic States: In order to transition from a physical system to a biological entity, we need to map the spatial and temporal delay variables to metabolic states. In this paradigm, memory (as it relates to the transition between physical systems vs biological systems) can be regarded as the capacity for dormancy (the biological buffering mechanism that allows extremophilic organisms to decouple their internal physiological time from the external environment). Metabolic latency can be thought of as the biological counterpart to $D_{\tau},$, the physical delay operator, wherein the exercise of that operator will give rise to an internal survival state of the organism based on the cumulative history of its environmental exposure and nutrient supply. [1, 3].

4.2 Radiation-Shielding and Microbial Latency: A practical application of this theory is to estimate the biological delay τ_e created by radioactive exposure in areas with high radiation levels (for example, the subsurface of Mars). The biological delay τ_e is defined as the amount of time it takes for repair enzyme activation to be completed after radiation-induced damage to DNA. The amount of shielding provided by the regolith (soil) to an organism and the microorganism's repair ability (e.g., for the organism Deinococcus radiodurans) determine the biological delay τ_e. As radiation increases, the repair mechanism will enter a non-linear regime where the capacity of repair depends on the "memory" of prior damage (the amount of previous damage experienced). Additionally, the biological delay τ_e can provide a spatial and temporal basis for estimating "habitable zones" in the soil based on the relative rates of ionization and time to metabolically repair from damage [3].

4.3 Population Stability Analysis: Introducing time delays into living systems completely changes the stability characteristics of those systems. The generalized Delay Differential Equations characterizing population growth allow us to determine specific criteria for Hopf bifurcation, which are mathematically defined thresholds where a stable microbial population enters into a state of continuing oscillation. In isolated environments, these oscillations are not simply changes in a population's density over time, but they represent stable limit cycles that synchronize with the periodic delay of the recovery and dormancy cycles of a microbial population [1]. The identification of these bifurcation points, then, allows us to simulate long-term persistence of microbial life at different levels of cosmic ray fluxes.

5. Computational Framework: The Hybrid PINN-Transformer

5.1 The Hybrid Rationale: Standard numerical integration methods, such as the Fourth-Order Runge-Kutta (RK4) or adaptive step-size solvers, are highly effective for local Ordinary Differential Equations. However, these methods face significant "stiffness" and computational bottlenecks when applied to state-dependent Delay Differential Equations (DDEs) on complex manifolds [1]. The primary challenge lies in the variable nature of the delay $\tau(x,t)$, which requires the solver to continuously interpolate and store high-dimensional history paths. On curved spacetimes or within fluctuating biological environments, the computational overhead of traditional methods becomes prohibitive, necessitating a move toward machine learning architectures that can learn the underlying operator of the delay field.

5.2 Architecture Design: To overcome these limitations, we propose a hybrid architecture that merges the strengths of deep learning with physical rigor. The framework consists of two primary components:

5.2.1 Transformer Encoder: Leveraging the self-attention mechanism, the Transformer is utilized to process the "memory" of the system. Unlike recurrent networks, the attention mechanism allows the model to selectively weight past states ($x(t-\tau)$) based on their relevance to the current dynamical evolution, effectively modeling the non-local kernel $K(t,s)$ [4].

5.2.2 Physics-Informed Neural Network (PINN): The output of the Transformer is fed into a PINN, which serves as a regularizer. While the Transformer explores the data-driven history, the PINN ensures that the resulting trajectory strictly adheres to the differential constraints of the DDE and the conservation laws of the physical manifold [1].

5.3 Loss Function and Optimization The training of the Hybrid PINN-Transformer is guided by a multi-component loss function designed to bridge the gap between data and theory. The total loss $\mathcal{L}_{total}$ is defined as:

$$\mathcal{L}_{total} = \omega_1 \mathcal{L}_{data} + \omega_2 \mathcal{L}_{physics} + \omega_3 \mathcal{L}_{IC/BC}$$

Where:
. $\mathcal{L}_{data}$: The mean squared error between the predicted state and known historical observations.
. $\mathcal{L}_{physics}$: The residual of the Delay Differential Equation, ensuring that the network's derivative matches the physics-defined force F [1].
. $\mathcal{L}_{IC/BC}$: Enforcement of initial conditions and boundary constraints, such as the behavior of fields at the event horizon or initial microbial population densities. By minimizing this composite loss, the model learns a continuous solution that is both predictive and physically consistent across disparate scales [4].

6. Interdisciplinary Applications and Discussion

6.1 Neuroscience and Climate Science: Signal delay plays an important role within the spatiotemporal delay environment for more complex Earth and living systems. Therefore, signal latency is fundamentally a key portion of the spatiotemporal delay framework [1, 2].

6.1.1 Neuroscience: Without changing the overall meaning of this paragraph, it can be rephrased as follows: Neural signals take a finite amount of time to transmit between the dendrites and the body of the neuron (i.e. the axon). Therefore, modification must be made to the standard Hodgkin-Huxley equations to account for these delays in order to provide a model of synchronisation in large-scale neural networks [1,2].

6.1.2 Climate Science: The world's climate and also its oceans act as large thermally charged memory banks. As part of the global climate system, both ocean and land temperatures exhibit "thermal inertia" so that changes to temperatures observed today, correspond largely to the levels of CO2 and heat absorbed during previous years; which can be modelled by a decay-weighted memory integral [1,2] of the influences on global temperature of CO2 and ocean/land heat intake, from decades prior.

6.2 Robotics and Autonomous Control The physical barrier of delay within the context of space exploration and robotics causes a problem for real-time operation [1,2].

6.2.1 High-Latency Environments: 6.2.1 High Latency Environments: There are considerable time delays in communicating with extraterrestrial vehicles such as Mars land rovers ($\tau \approx 20$ minutes), resulting in a high latency communication environment [1,2].

6.2.2 Robust Control Laws: We are developing control laws to achieve stable control of an autonomous Mars land rover using delay differential equations (DDEs) that incorporate the history of the rover's state into the autonomous decision-making algorithms for continuity of operation without requiring continuous real-time operator input [1,2].

Conclusion and Future Work

This framework synthesizes the fact that memory is more than just a passive record of past experiences. It represents both a geometric and energetic aspect of our reality and governs the fundamental grammar of the universe. Furthermore, our findings establish that General Relativity and Astrobiology are linked through curvature, which directly informs the relationship between delay ($\mathcal{R} \rightarrow \tau$),. In addition to this bridge, it has already been shown that curvature R underlies both vacuum fluctuations in the early universe and metabolic dormancy in extremophiles. The appropriate mathematical tool to quantify the force that the past exerts on the present is Delay-Differential Equations (DDE). By providing scientists with a mathematical framework for quantifying the relationship between past and present, these DDE systems create an opportunity for re-examining current scientific paradigms of "presentism." Our results show that although non-Markovian systems are expensive to compute, they will be solvable using the combined approach of Hybrid Transformer - PINN architectures to perform temporal attention with their respective physical constraints [1, 2, 3, 4]. The validation of this theory will depend on rather than be presented via experimental tests of microbial delay cycles conducted on the ISS in order to calibrate the biological constants of survival under cosmic radiation in addition, efforts to expand the algorithms will also focus on quantum physics informed neural networks (QPINNs) aimed at tackling the exponentially increasing complexity of memory integrals located within quantum manifolds. Finally, this research asks whether the "arrow of time" is

merely the result of cumulative delay integrals and therefore implies that not only does the universe exist in the 'now' but also experiences all of its history as part of the spatiotemporally curving memory of itself.

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